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An adaptive fuzzy network for control of manipulating robot dynamic behavior

by

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Abstract: In this paper is considered the problem how to achieve a specific dynamic behavior of robot end-point from the aspect of impedance control and actuation redundancy. The target impedance is analytically formulated. Due to its complexity, analytical formulation is not suitable for real-time application. To overcome this problem, a simple fuzzy model of isotropic impedance in the form of adaptive fuzzy network is proposed. This model is incorporated in the general form of impedance control law, so that a new fuzzy-impedance control law is obtained. Verification of the proposed control law is provided by computer simulation, taking as example 2-d.o.f. manipulating robot.

Keywords: adaptive fuzzy network, fuzzy dynamic model, impedance control, manipulating robots

1. Introduction

Control of dynamic behavior of manipulating robots is one of the most challenging problems in designing intelligent robotic systems. For any given application, manipulating robot should be able to provide corresponding dynamic behavior. In the case of robotic assembly, isotropic behavior is found to be one of the most important mechanical properties of the manipulating robot. Mechanical isotropy means a collinearity of the contact force vector and the vector of corresponding movements of parts to be assembled. If isotropy exists close to the tip of the peg, irregularities as jamming and wedging will not occur Whitney, (1982). In the following text the control of dynamic behavior of manipulating robots will be considered through the problem of producing mechanical isotropy of robot end-point.

Generally, there are two different concepts to achieve isotropic behavior of manipulating robots. The first one is based on special devices which may be added to the manipulating robot end-point. Remote Center of Compliance unit (RCC) is the most successful example of this concept Whitney, (1982). Despite good mechanical properties, practical application of this concept is limited due to the insufficient flexibility (RCC unit is purely mechanical and always adjusted for particular task in robotic assembly). The more flexible concept is based on isotropic properties which manipulating robot provides itself i.e., by its own mechanical structure. The problem here is a limited number of robot postures for which isotropic behavior exists, as a result of passive compliance derived from flexibility of joints. Selective Compliance Assembly Robot Arm - SCARA, Makino and Furuya (1980) is typical example of this concept. For SCARA robot configuration isotropy exists for one specific posture only Bourrieres, Jeannier and Lhote (1984). This problem may be solved by active adaptation of joint compliance achieved through specific behaviour of robot control system.

2. Impedance control and isotropic target impedance

Contrary to passive compliance derived from structural flexibility, active compliance of manipulating robot may be achieved by adjusting the loop gains of servo actuators. Several linear and nonlinear control methods may be used to develop compliance control. The survey of these methods is briefly discussed in Whitney (1987), where generalized stiffness control, generalized damper control, hybrid force-position control and impedance control are recognized. All these methods refer to implicit force control. Sensory force information is used in the controlled feedback loop for active accommodation of interacting forces through the correction of programmed end-point position or programmed end-point velocity, without explicitly specified programmed force.

2.1. Impedance control law

The paper pays special attention to the mechanical impedance control law Hogan (1985). Distinction between the impedance control and the previously mentioned variant methods is the attempt of the controller to implement dynamic relation between manipulator variables such as end-point position and force, rather than control of these variables alone. The target impedance may be specified in task coordinates, through three characteristic dynamic parameters: generalized stiffness, generalized damper and generalized inertia. By specifying these parameters, we specify at the same time the desired dynamic behavior of manipulating robot.

The dynamic model of manipulating robot constrained motion is given by Craig (1986), Vukobratović and Ekalo (1993):

$$H(q)\ddot{q} + h(q, \dot{q}) = \tau - J^T(q)F \ , \tag{1}$$

where: q is the vector of robot generalized coordinates, $H(q)$ is the robot inertial matrix, $h(q, \dot{q})$ is the vector of nonlinear functions which include centrifugal, Coriolis and gravitational terms, τ is the vector of joint torques, $J(q)$ is the Jacobean matrix, and F is the vector of external force imposed at robot end-point. Applying duality principle Hogan (1985), the target impedance of the entire robot - environment system should be of the second order:

$$F = M\left(\ddot{X} - \ddot{X}_p\right) + B\left(\dot{X} - \dot{X}_p\right) + K\left(X - X_p\right) \ , \qquad (2)$$

where M, B and K are the target inertial matrix, damping matrix and stiffness matrix expressed in Cartesian coordinates. Superimposing (1) and (2), leads to the impedance control law in the Cartesian coordinate frame:

$$F^G = G(q)\left[\ddot{X}_p + M^{-1}\left(-B\dot{E} - KE + F\right)\right] + h^G(q,\dot{q}) - F \ , \qquad (3)$$

where: F^G is the generalized actuation force vector (fictitious actuator placed at the robot end-point), $G(q)$ is the generalized inertial matrix in respect of the robot end-point (effective mass, described in Asada and Ogawa (1987), $h^G(q,\dot{q})$ is the generalized vector of nonlinear functions, and $E(q,t) = X - X_p$ is the error function where subscript p denotes the prescribed (programmed) values.

2.2. Isotropic target impedance

Essentially, isotropy connotes equal properties in all directions. Paradigms of isotropy are Platonic solids. The cube, as a rigid body of uniform density, is one of Platonic solids. If we excite such a cube to rotate about a certain axis in space, the body will continue rotating about the same axis and no motion will arise about other ones. Isotropy may be also attributed to multi-d.o.f. (degrees of freadom) manipulating robots in kinetostatic sense, if such structures are recognized as black-box that transforms the external excitation, acting on robot end-point (excitation point), in internal joints torques of robot kinematic chain, resulting in A superposed corresponding movement of robot end-point Angeles (1995).

The problem of isotropic behavior of manipulating robots is discussed in Angeles (1995), where quasi-static and kinematics isotropy are identified. To achieve isotropic behavior of robot end-point we propose the following target impedance parameters Petrović and Milačić (1996):

$$M = J^{-T}(q)H(q)J^{-1}(q) = G(q) \ , \qquad (4)$$

$$B^2 - 4KM = 0 \ , \qquad (5)$$

$$K = \mathrm{diag}\left[k_T, k_T, k_T, k_R, k_R, k_R\right] \ . \qquad (6)$$

These parameters are derived from considerations described below.

For the robot in rest (zero end-point velocity), the following are satisfied: $E = const \rightarrow \dot{E} = 0$, $\ddot{X} = 0$, and $h^G(q,\dot{q})$, so that the control law (3) becomes:

$$\bar{F}^G = -G(q)M^{-1}KE + G(q)M^{-1}F - F \ . \qquad (7)$$

By substituting (4) in (7) the following is obtained:

$$\bar{F}^G = -KE = K(X - X_p). \tag{8}$$

The physical meaning of the equation (8) is that if target stiffness matrix K satisfies (6) then generalized actuation force vector will be collinear to the end-point displacement vector, or analytically expressed:

$$F \times \delta X \equiv 0 \ . \tag{9}$$

This is a necessary condition for quasi-static isotropy. Besides this, there is another important consequence of equation (8).

Impedance control law may be expressed in generalized (joint) coordinates of manipulating robot, so that equation (8) becomes:

$$\tau = J^T(q)KJ(q)(q - q_p) = K^q(q)\eta \ , \tag{10}$$

where $\eta(q,t) = q - q_p$ is the error function. The member $J^T(q)KJ(q) = K^q(q)$ is the stiffness matrix K expressed in manipulating robot generalized (joint) coordinates. This matrix is always symmetric, positive definite and, in general, non diagonal. Because the matrix K^q represents stiffness of joint actuators, in the case of nonredundant actuation this matrix must be diagonal. It is clear that this condition is very restrictive, so the isotropy exists only under specific geometrical relations in kinematic chain and for a very few number of robot postures Bourrieres, Jeannier and Lhote (1984). Equation (8) is equivalent to equation (10) but, from the aspect of impedance control law (3), it is not so restrictive. In this case any nondiagonal may be realized electronically. According to (8) and (10) we can write:

$$\begin{aligned} KE = J^T(q)KJ(q)\eta = K^q\eta \rightarrow \\ \bar{\tau}_i = K^q_{i,1}\eta_1 + \cdots + K^q_{i,i}\eta_i + \cdots + K^q_{i,n}\eta_n = \textstyle\sum_{j=1}^{n} K^q_{i,j}\eta_j \ . \end{aligned} \tag{11}$$

Cross terms in (11) generate electronic coupling between joints equivalent to mechanically realized actuation redundancy observed in biomechanical systems. For previously mentioned 2-d.o.f. SCARA robot arm, electronic coupling defined by (11) is mechanically equivalent to the actuation system shown in Fig. 1. Cross term $K^q_{1,2}$ denotes stiffness of third (redundant) actuator which simultaneously actuates both joints with $\tau_{1,2}$ driving torque. This additional actuator plays a very important role because it compensates weakness of non-redundant actuated robot chain.

Target damping matrix B is chosen according to the critical damping condition and no other analytical relations are formulated for kinematic isotropy. Further research is needed.

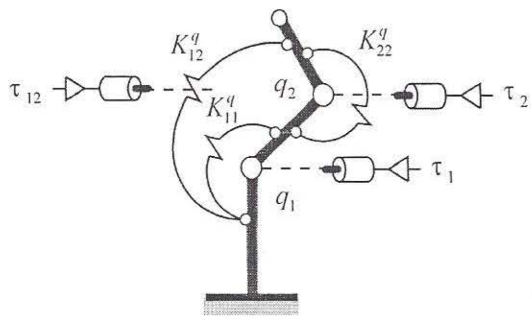


Figure 1. Mechanical actuation redundancy for 2-d.o.f. robot arm defined by Eq. (11).

3. Fuzzy model of isotropic target impedance

Impedance control law (3) is based on the manipulating robot dynamic model which is highly non-linear second order model. The dynamic phenomena which follow constrained motion, require short sampling time in digital control system, approximately 1 ms or less. This requirement is disproportional to necessary calculations and hard to realize in practice. To solve this problem, the fuzzy set theory and approximate reasoning are used for modeling isotropic impedance (4), (5), and (6), in more efficient way than the analytical one.

Fuzzy model of isotropic target impedance should be fuzzy dynamic formal structure with m inputs and n outputs, which maps input vector $X = X(t)$, $X \epsilon R^{m\times 1}$ into output vector $Y = Y(t)$, $Y \epsilon R^{n\times 1}$. With regard to: $q = q(t)$, $q \epsilon R^{n\times 1}$, $\eta = \eta(t)$, $\eta \epsilon R^{n\times 1}$, $\dot{\eta} = \dot{\eta}(t)$, $\dot{\eta} \epsilon R^{n\times 1}$ and , $F = F(t)$, $F \epsilon R^{n_e\times 1}$ number of inputs is $m = 3n + n_e$ (n denotes the number of actuated joints while n_e is environment dimension).

Functional relationships to be represented by the fuzzy model are complex and highly nonlinear, so learning time may generally become extremely long. Part of difficulty arises from size of sample training space. Let's consider another simple case of 2-d.o.f. SCARA robot arm. If, for example, $k = 10$ samples are required in each dimension, the total number of required training samples would be $N = k^{4n} = 10^8$. The number of required samples becomes astronomically large for 6-d.o.f. manipulating robot arm. It is clearly unrealistic.

The context sensitive fuzzy model represents one possible answer to this problem. Isotropic target impedance may be decomposed into a large number of low order subsystems. These subsystems require a small number of training samples and reduce convergence time.

3.1. Functional decomposition of control law

The first step in target impedance fuzzy modeling is functional decomposition of impedance control law (3). Expressing (3) in generalized coordinates, we suggest decomposition in the following way:

$$\tau^G = H(q)\left[\ddot{q} + P(\eta,\dot{\eta}) + Q(q,F)\right] + h(q,\dot{q}) - J^T(q)F \ , \tag{12}$$

where: $P(\eta,\dot{\eta})$ is an n-dimensional vector function of robot transient processes, $Q(q,F)$ is an n-dimensional vector function which represents the dynamic interaction of robotic manipulator with the environment.

Vector function P may be adopted in the form:

$$\begin{aligned} P(\dot{\eta},\eta) &= P^1(q,\dot{\eta}) + P^2(q,\eta) \ , \\ P^1(q,\dot{\eta}) &= -J^{-1}(q)M^{-1}BJ(q)\dot{\eta} = \Gamma^1(q)\dot{\eta} \ , \\ P^2(q,\eta) &= -J^{-1}(q)M^{-1}KJ(q)\eta = \Gamma^2(q)\eta \ , \end{aligned} \tag{13}$$

where $\Gamma^1(q)$ and $\Gamma^2(q)$ are the nonlinear matrix functions. In the same way, function Q may be represented as:

$$Q(q,F) = J^{-1}(q)M^{-1}F = \Lambda(q)F \ . \tag{14}$$

Now, the reformulated target impedance is expressed with matrix functions $\Gamma^1(q)$ and $\Gamma^2(q)$ and $\Lambda(q)$, which, for isotropic target impedance given by (4), (5) and (6) are defined as:

$$\Gamma^1(q) = -H^{-1}(q)J^T(q)B(q)J(q) \ , \tag{15}$$

$$\Gamma^2(q) = -H^{-1}(q)J^T(q)KJ(q) \ , \tag{16}$$

$$\Lambda(q) = H^{-1}(q)J^T(q) \ . \tag{17}$$

Matrix functions (15), (16) and (17) physically represent nonlinear gains in controlled feedback loops (see Fig. 2). This is a *primary decomposition.*

Decomposition of matrix functions (15), (16) and (17) is *secondary decomposition.* Each of them consists of n^2 elements which are nonlinear functions of generalized coordinates: $\Gamma^1_{i,j} = \Gamma^1_{i,j}(q_1,\cdot,q_n)$. Matrix elements should be modeled separately. For example, according to adopted secondary decomposition, vector function $P^1(q,\dot{\eta})$ may be expressed as follows:

$$\begin{aligned} P^1(q,\dot{\eta}) &= \begin{bmatrix} \Gamma^1_{(1,1)} & \Gamma^1_{(1,2)} & \cdots & \Gamma^1_{(1,n)} \\ \Gamma^1_{(2,1)} & \Gamma^1_{(2,2)} & \cdots & \Gamma^1_{(2,n)} \\ \vdots & \vdots & \ddots & \vdots \\ \Gamma^1_{(n,1)} & \Gamma^1_{(n,2)} & \cdots & \Gamma^1_{(n,n)} \end{bmatrix} \begin{bmatrix} \dot{\eta}_1 \\ \dot{\eta}_2 \\ \vdots \\ \dot{\eta}_n \end{bmatrix} = \\ &\begin{bmatrix} \Gamma^1_{(1,1)}\dot{\eta}_1 + \Gamma^1_{(1,2)}\dot{\eta}_2 + \cdots + \Gamma^1_{(1,n)}\dot{\eta}_n \\ \Gamma^1_{(2,1)}\dot{\eta}_1 + \Gamma^1_{(2,2)}\dot{\eta}_2 + \cdots + \Gamma^1_{(2,n)}\dot{\eta}_n \\ \vdots \\ \Gamma^1_{(n,1)}\dot{\eta}_1 + \Gamma^1_{(n,2)}\dot{\eta}_2 + \cdots + \Gamma^1_{(n,n)}\dot{\eta}_n \end{bmatrix} = \begin{bmatrix} P^1_1 \\ P^1_2 \\ \vdots \\ P^1_n \end{bmatrix} \end{aligned} \ . \tag{18}$$

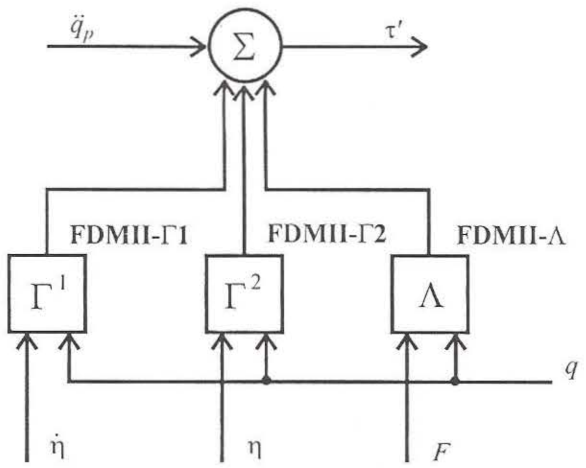


Figure 2. Primary decomposition of isotropic target impedance on three sub-models.

The other vector functions $P^2(q, eta)$ and $Q(q, F)$ may be expressed on the same way.

3.2. Adaptive fuzzy model

Matrix elements may be modeled by adaptive fuzzy network ANFIS Jang (1993) (Fig. 3). This adaptive fuzzy network is of feedforward type and consists of square and circle nodes, placed in five layers. Links between nodes indicate the flow direction of signals only and no weights are associated with links. Square nodes have parameters and they are adaptive, while circle nodes are fixed and they perform basic functions of Sugeno-Takagi fuzzy inference Sugeno and Kang (1988). To achieve the required input-output mapping, the parameter set of an adaptive network is updated according to the given training data and adopted learning algorithm.

The adaptive network (Fig. 3) works as the first order Sugeno-Takagi fuzzy dynamic structure with inference in form of generalized modus ponens:

$$\textbf{if } (q_1 \textbf{ is } \tilde{A}^1) \textbf{ and } (q_2 \textbf{ is } \tilde{A}^2) \textbf{ then } \Gamma^1(i,j) = aq_1 + bq_2 + c\,, \tag{19}$$

where: $\tilde{A}^1$ and $\tilde{A}^2$ are the fuzzy sets of antecedents (fuzzy labels), q_1 and q_2 are the input crisp variables, $\Gamma^1(i,j)$ is the output variable and a, b and c are the consequent parameters. The consequent variables are fuzzy singleton sets whose singleton output spikes may walk around the output space, in dependence on the crisp input values. This fuzzy dynamic structure has high representative capabilities and computational efficiency, which is of particular importance to the problem in hand.

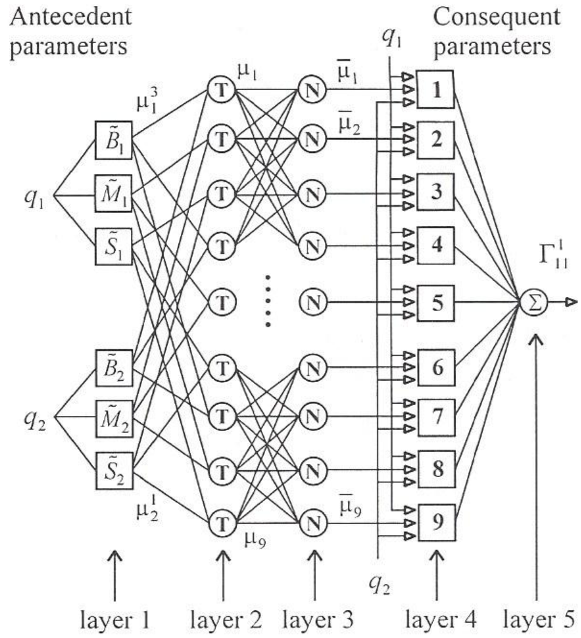


Figure 3. An adaptive fuzzy network for modeling elements of matrix functions.

Learning algorithm is based on *batch learning paradigm* (on-line learning). The parameters set of adaptive network is updated after the whole training data set has been presented, i.e., only after the each *training epoch*. Hybrid learning rule which combines gradient decent method and the least squares estimate (LSE) are used for identification of network parameter set. Each epoch of this hybrid learning procedure is composed of a forward pass and a backward pass. In the forward pass, input data and functional signals go forward to calculate each node output and, with sequential LSE, identify a set of consequent parameters. In the backward pass, the error rates propagate from the output end toward the input end, and the antecedent parameters are updated by the gradient decent method. Applied hybrid learning rule not only can decrease the dimension of the search space in the gradient method, but, in general, also speed up the convergence of learning algorithm. Details may be found in Jang (1993).

Applying the same approach, it is possible to build up a super dynamic structure in the form of an adaptive fuzzy network for representing vector functions $P^1(q,\dot{\eta})$, $P^2(q,\eta)$ and $Q(q,F)$. An example is shown in Fig. 4. Three layer network represents the first element of vector function $P^1(q,\dot{\eta})$. Square nodes have parameters too, but in that case, they are a five layer adaptive networks shown in Fig. 3.

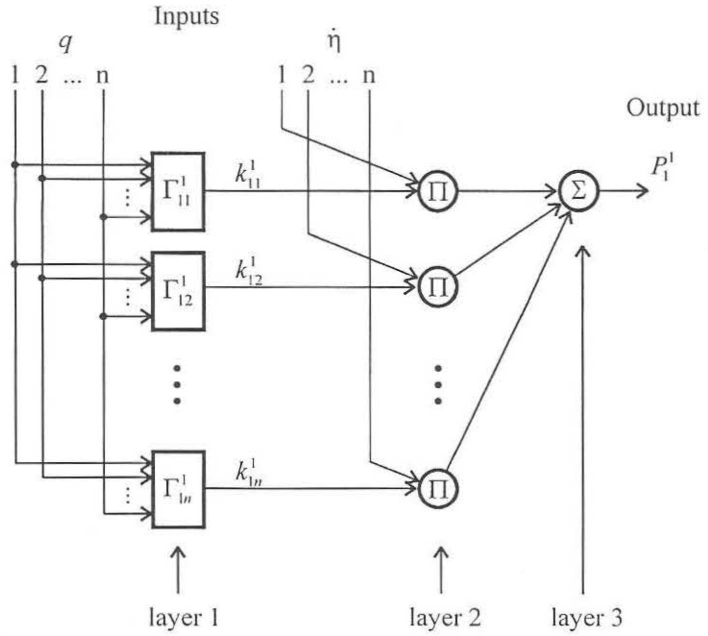


Figure 4. Adaptive fuzzy network which represents the first element of vector function $P^1(q, \dot{\eta})$ according to the adopted secondary decomposition of isotropic target impedance.

4. Simulation example

To verify the proposed fuzzy-impedance control law, computer simulation was performed in MATLAB SIMULINK environment with the additional FUZZY toolbox. Simple 2-d.o.f. SCARA robot in horizontal plane was used as an example. For simplicity, all mass exists as a point mass at the distal end of each link. Dynamic equations of this robot may be found in Craig (1986). Lengths of the robot links satisfy passive isotropy condition $l_1/l_2 = \sqrt{2}/2$ given in Bourrieres, Jeannier and Lhote (1984).

As example, Fig. 4 shows four elements of matrix function Γ^1 which are defined by equation (15). All matrix elements are nonlinear functions of the robot generalized coordinates.

Joint angles are adopted as antecedent linguistic variables with the names $'q_1\,'$ and $'q_2\,'$. The term sets of antecedent variables are based on the uniform grid partition of the input space on three fuzzy values only:

$$\begin{aligned} T(L^1) &= T(q_1) = \{'Left\,', \ 'Center\,', \ 'Right\,'\} \\ T(L^2) &= T(q_2) = \{'Small\,', \ 'Medium\,', \ 'Large\,'\}\,. \end{aligned} \tag{20}$$

Two types of membership functions are used for antecedent fuzzy sets: linear, in the triangular form, defined as:

$$\mu(q;a,b,c) = \begin{cases} 0 & q \le a \\ \frac{q-a}{b-a} & q \le q \le b \\ \frac{c-q}{c-b} & b \le q \le c \\ 0 & c \le q \end{cases}, \tag{21}$$

and nonlinear, in the form of generalized bell function, defined as:

$$\mu(q;a,b,c) = \frac{1}{1 + \left|\frac{q-c}{a}\right|^{2b}}. \tag{22}$$

For both cases membership functions are specified by three parameters.

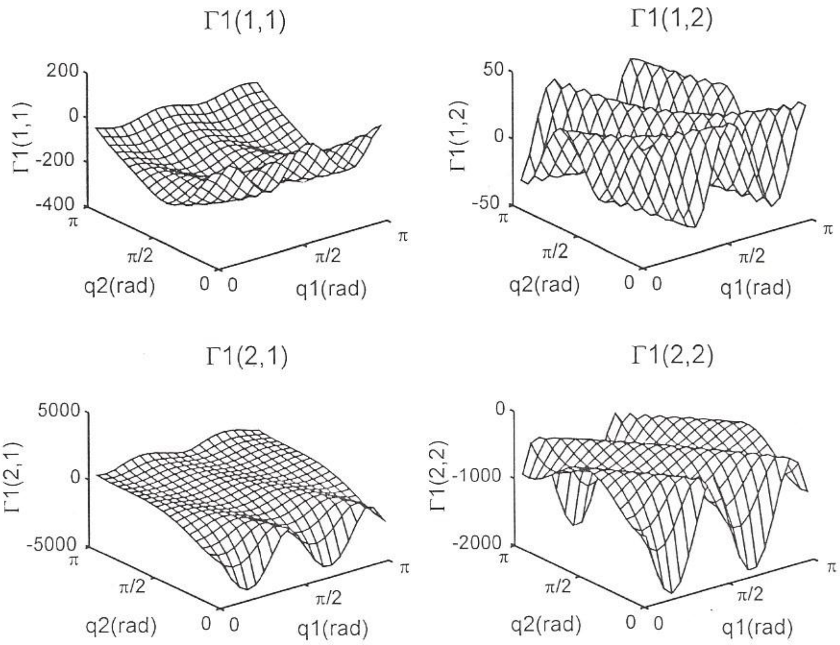


Figure 5. The nonlinear elements of the matrix function $\Gamma^1_{(1,1)}$, analytically formulated by (15) - nonlinear gains in the speed feedback loop.

In accordance with (20), nonlinear elements of matrix functions Γ^1, Γ^2 and Λ are described by linguistic models with nine Sugeno-Takagi rules of the form (19). In the case of matrix element $\Gamma^1_{(1,1)}$, the linguistic model is:

R_1 : **if** (q_1 **is** *Left*) **and** (q_2 **is** *Small*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_1$)
R_2 : **if** (q_1 **is** *Left*) **and** (q_2 **is** *Medium*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_2$)
R_3 : **if** (q_1 **is** *Left*) **and** (q_2 **is** *Large*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_3$)
R_4 : **if** (q_1 **is** *Center*) **and** (q_2 **is** *Small*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_4$)
R_5 : **if** (q_1 **is** *Center*) **and** (q_2 **is** *Medium*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_5$)
R_6 : **if** (q_1 **is** *Center*) **and** (q_2 **is** *Large*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_6$)
R_7 : **if** (q_1 **is** *Right*) **and** (q_2 **is** *Small*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_7$)
R_8 : **if** (q_1 **is** *Right*) **and** (q_2 **is** *Medium*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_8$)
R_9 : **if** (q_1 **is** *Right*) **and** (q_2 **is** *Large*) **then** ($\Gamma^1(1,1)$ **is** $\Gamma(1,1)\_9$)

Identification of 45 parameters is needed to model each matrix element. Isotropic fuzzy-impedance model for SCARA robot have 12 Sugeno-Takagi fuzzy models of matrix elements, giving a total number of 540 parameters. The set of 400 i/o data pairs for each matrix element is used for training the corresponding fuzzy network. Fig. 6 shows initial and optimized nonlinear membership functions after 100 training epochs for matrix element $\Gamma^1_{(1,1)}$.

For the same matrix element, the error convergence graph is shown on Fig. 7. The form of antecedent membership functions has an important role. The fuzzy model with nonlinear membership functions (nonlinear fuzzy model) has better representative capabilities and enables faster learning. Relative RMS error of value 0.04 is obtained after 300 epochs of training. That may be accepted as a very good approximation, especially if a rough input space partition on three fuzzy values is considered.

The quality of the proposed isotropic fuzzy-impedance control may be easily tested by simple simulation experiment. The manipulating robot has a predefined fixed posture in working space, defined by $q_p(t) = q_p(t_0)$, and no motion of robot end-point is programmed. The robot excitation is performed by external force impulse applied on the robot end-point. The force impulse is a known function of time $F = F(t)$, with specified acting direction and with unit intensity. The force impulse duration is chosen to be 200 ms. This experiment is a very good approximation of real situations which happen in part mating process. Also, excitation is basically dynamic, which is important for analysis of influence of target impedance parameters on dynamical behavior of manipulating robot arm.

Fig. 8 shows the robot end-point response in the case of rectangular form of impulse force excitation for robot posture defined by $q = [0, \pi/12]^T$ and force acting angle $\beta = \pi/2$. Despite the fact that the chosen robot posture is very close to the robot outer singularity, with presence of robot highly nonlinear dynamics, control system is stable and working very well. Fig. 9 shows robot end-point displacement for four characteristic excitation angles for the same robot posture and impulse shape.

The best way to get insight of the quality of proposed isotropic fuzzy-impedance control is *the compliance map* shown in the Fig. 10. The compliance map represents the miscolinearity angle as a function of robot posture defined by generalized coordinate q_2 and the excitation force angle β. As it shown

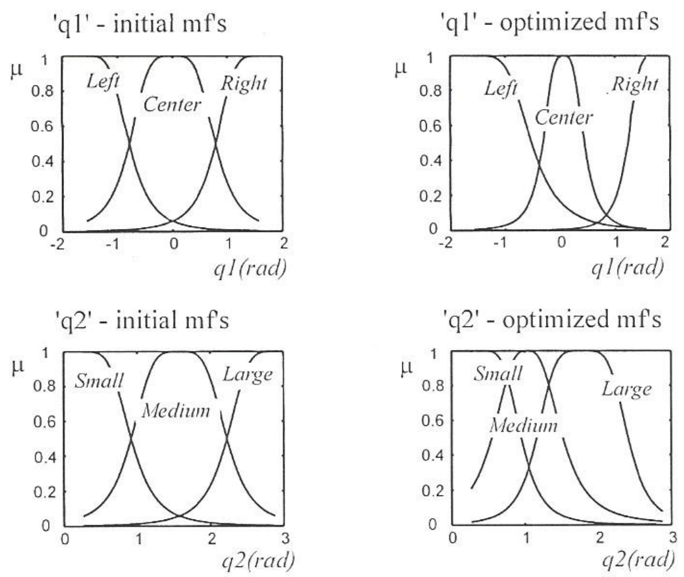


Figure 6. Initial and optimized membership functions for matrix element $\Gamma^{1}_{(1,1)}$ after 100 epochs of training.

in Fig. 10, structural isotropy for SCARA robot exists only for the posture defined by $q_2 = 3\pi/4$ Bourrieres, Jeannier and Lhote (1984). The proposed fuzzy-impedance control law enables approximate isotropic behavior in the entire working space, except in the zones close to the singularities (note, though, that the scales of the vertical axis used in 3-d graphs shown in the Fig. 10, are not the same).

5. Conclusion

The simulation results clearly demonstrate that the proposed fuzzy-impedance control law may produce isotropic behavior of manipulating robot although this isotropy does not exist in mechanical structure only. Isotropy is produced in the way equivalent to mechanical actuation redundancy (one actuator simultaneously actuate more than one joint). This kind of redundancy is common in biomechanical systems. First order Sugeno-Takagi fuzzy model and input space partition on three linguistic values are acceptable for isotropic target impedance modeling. The hybrid learning algorithm used is stable and has good convergence. Antecedent linguistic values with nonlinear membership functions give higher accuracy of fuzzy model and faster convergence of learning algorithm.

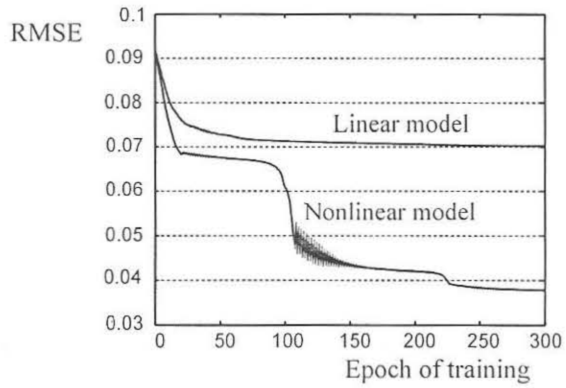
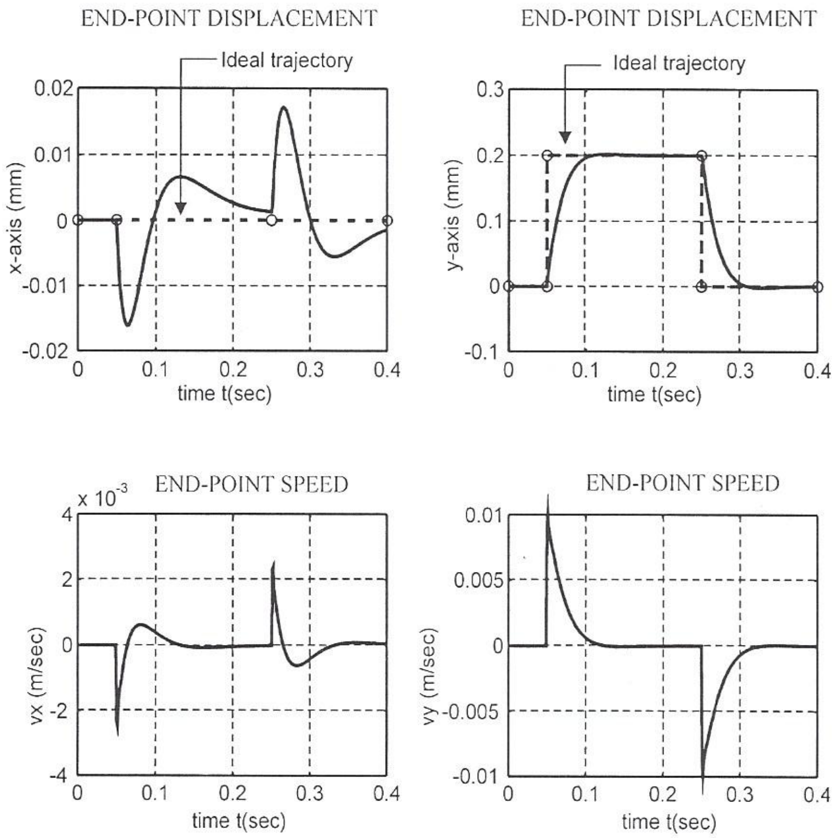


Figure 7. RMS error convergence and learned surface for matrix element $\Gamma^1_{(1,1)}$.



Prescribed lateral stiffness: $K_X = dijag[5000 \quad 5000]$, (N/m)
Nominal posture: $q_o = [0 \quad \pi/12]^T$
Force acting direction: $\beta = \pi/2$

Figure 8. The robot end-point response in the case of excitation with the rectangular force impulse applied on the robot end-point having a posture close to the outer singularity.

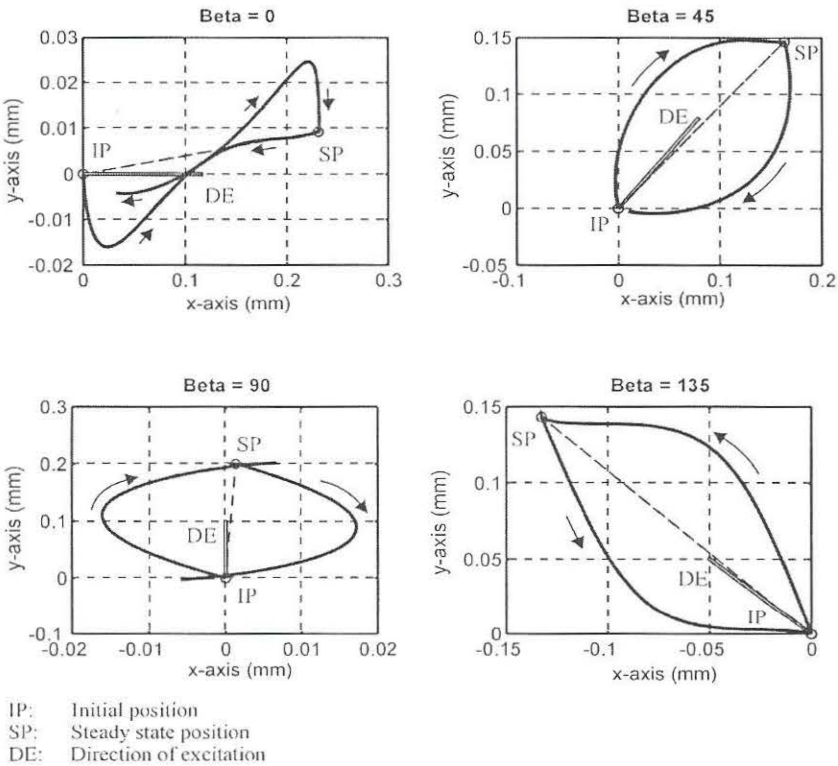


Figure 9. The robot end-point displacements for different acting angles of the excitation force.

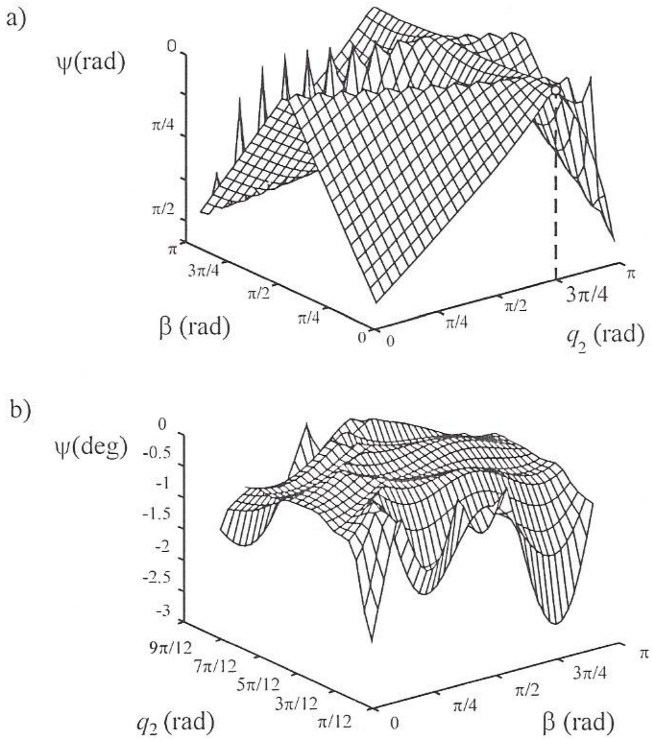


Figure 10. The compliance map of SCARA robot achieved by: a)Passive structural compliance and b)Isotropic fuzzy-impedance control law.

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